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IS THE BOX-COX TRANSFORMATION NEEDED IN MODELING TELKOM'S STOCK PRICE USING NNAR AND DESH METHODS?

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Abstract: Accurate stock price forecasting requires appropriate preprocessing, particularly for time series data with high variability and nonlinear patterns. This study investigates whether applying the Box-Cox Transformation (BCT) improves forecasting performance when modeling Telkom Indonesia's stock price using Neural Network Autoregressive (NNAR) and Double Exponential Smoothing Holt (DESH) methods. The NNAR model architecture is selected based on nonlinearity testing of lag variables, while DESH parameters are optimized by minimizing mean square error. Forecasting accuracy is evaluated using Mean Absolute Percentage Error (MAPE), root Mean Square Error (RMSE), and Mean Percentage Error (MPE), comparing models built with and without BCT. Results show that BCT does not enhance forecasting accuracy for either NNAR or DESH. Moreover, the NNAR model without BCT outperforms DESH, producing approximately 50% lower MAPE, RMSE, and MPE values on the testing dataset. These findings suggest that BCT may not be necessary for time series modeling in this case, and NNAR without transformation is recommended for forecasting Telkom's stock price.

1. INTRODUCTION

Stocks represent ownership in a company and contain information such as nominal value, company name, and the rights and obligations of the holder (Fahmi, 2014; Setiawan & Rosa, 2023). Stock prices are often viewed as indicators of a company's management success, where rising prices suggest strong business performance. Among Indonesian investors, PT Telkom Indonesia's stock is highly sought after due to its consistent annual price increases (Rezaldi & Sugiman, 2021). PT. Telkom Indonesia is an Indonesian state-owned enterprise that engaged in communication services, information technology services, and telecommunications networks since July 6, 1965. PT Telkom Indonesia has 52.09% of its shares held by the Government of Indonesia, while the remaining 47.91% are owned by the public (Telkom Indonesia, 2023).

Financial time series data, including stock prices, are typically characterized by nonlinearity, high volatility, and complex dynamics. Therefore, linear models are generally unsuitable for modeling such data (Adebiyi et al., 2014; Hossain et al., 2020; Kim & Won, 2018; Patel et al., 2015). Previous studies on Telkom stock price forecasting have applied models such as ARCH-GARCH (Marvilia, 2013), fuzzy time series (Sihombing & Dahlia, 2022), and ARIMA (Rezaldi & Sugiman, 2021). However, none have specifically explored the use of Neural Network Autoregressive (NNAR) models, despite the data's apparent nonlinear structure.

NNAR, a forecasting method based on artificial neural networks (ANN), is well-suited for modeling complex nonlinear relationships without assuming linearity. Prior studies have shown NNAR's strong performance in different forecasting tasks, such as per capita income prediction (Sena & Nagwani, 2016) and COVID-19 infection fatality rate trends (Ansari Saleh & Boj, 2021), outperforming traditional statistical models.

In addition to model selection, preprocessing techniques such as Box-Cox transformation (BCT) are often recommended to stabilize variance and approximate normality in time series data, thereby potentially improving forecast accuracy (Lee et al., 2013; Nwakuya & Nwabueze, 2018; Proietti, 2014). However, the impact of applying BCT specifically in the context of stock price forecasting using NNAR and Double Exponential Smoothing Holt (DESH) models remains unclear.

This study aims to investigate whether the Box-Cox transformation improves forecasting accuracy when modeling Telkom's stock price using NNAR and DESH methods. Model performance is evaluated using Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Percentage Error (MPE). Given the importance of accurate forecasting in financial decision-making and the critical role of data preprocessing, this research addresses a gap in the literature by assessing the necessity of transformation in nonlinear time series modeling.

2. LITERATURE REVIEW

Based on the underlying calculation technique, there are two forecasting methods, i.e., classical and non-statistical methods (Son et al., 2020). Classical methods are built on mathematical equations with a specific assumption where the parameters of the model are estimated from the observed data to predict future values. These methods include Regression, ARIMA, Regression-seasonal ARIMA-GARCH, Exponential Smoothing (ES), Trigonometric-BCT (Box-Cox Transformation)-ARIMA-Trend and Seasonal components (TBATS), and Kalman Filters. In contrast to classical forecasting models, there are artificial intelligence-based non-statistical forecasting methods that generally have high accuracy and are more suitable for forecasting nonlinear and nonstationary data because of their nonlinear and nonparametric characteristic functions (Son et al., 2020; Sulandari et al., 2023). Some examples of these methods are CNN (Convolutional Neural Networks), Long Short-Term Memory, Radial Basis Function Neural Networks, and NNAR (Neural Network Autoregressive).

Exponential smoothing (ES) is a classic forecasting method that focuses on exponentially weighted observations. The success of ES in time series modeling can be seen in Dudek et al. (2021), Rendon-Sanchez & de Menezes (2019), Smyl (2020), Yonar et al. (2020), etc. Moreover, many researchers developed this method to handle more complex time series (see Taylor & Snyder (2012), Arora & Taylor (2013), Bernardi & Petrella (2015), Sulandari et al. (2016), etc). This method even became popular after winning the M5 competition (Smyl, 2020). A review of the development of this method on time series data with multiple seasonal patterns can be found in Sulandari et al. (2021). In this work, DESH can smooth the trend pattern found in Telkom stock price by choosing the right smoothing constants for level and trend (Nazim & Afthanorhan, 2014). Alias et al. (2016) compared the DESH method with ARIMA on linear trend data of housing demand population in Johor and obtained that DESH method is better with MAPE value of 1.522%. In Other study, Zaini et al. (2020) compared DESH method with Artificial Neural Network (ANN) on Malaysian banking closing price data and obtained that the DESH method is better compared with NNAR. However, it can be a different result when we work on other data sets, including the Telkom stock price.

2.1. Neural Network Autoregressive (NNAR)

The NNAR model is a nonparametric forecasting model which is suitable for forecasting complex nonlinear data. In NNAR model, the lagged values are used as inputs for the NNAR, similar to the use of lagged values in linear autoregression models. In general, the NNAR model, denoted by NNAR(p, k), has two parameters, i.e., p which represents the number of inputs and k which shows the number of units in hidden layer (Hyndman & George, 2018).

The NNAR forecasting model is constructed through two main steps. First, the autoregression order must be determined, indicating the number of lagged observations that are related to the current value in the time series. Unlike ARIMA, where the autoregressive order is typically selected based on criteria such as AIC or PACF plots under linear assumptions, the input selection for NNAR in this study is guided by a nonlinearity test using the White test (Prabowo et al., 2020). The White test is applied to the lagged variables to assess their nonlinear relationship with the response variable, ensuring that only significant and meaningful lags are included as inputs for the neural network model. In the second step, the NNAR model is trained on the selected lagged inputs using the training data. Thus, the order p in NNAR corresponds to the number of lagged inputs identified as important through the nonlinearity testing, differentiating the input construction process of NNAR from that of ARIMA, despite both being influenced by past observations.

2.2. Double Exponential Smoothing Holt (DESH)

The Exponential Smoothing (ES) method works based on averaging exponentially past observations of a time series (Sulandari et al., 2021). The most recent data is given the greatest weight with a decreasing value of the weight of the previous observation (Hyndman & Athanasopoulos, 2018). One type of ES forecasting method is DESH. This method can smooth the trend and gradient in the time series by using smoothing constants. Forecasting with this method is obtained using Equations (1-3).

$$L_t = \alpha Y_t + (1 - \alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \tag{2}$$

$$\hat{Y}_{t+h} = L_t + hT_t \tag{3}$$

where L_t: smoothed value of actual data at t; Y_t: observation value of actual data at t; α: smoothing value for level (0< α <1); β: smoothing value for trend estimation (0< β <1); T_t: trend estimation at t; $\hat{Y}_{t+h}$: forecasting for h upcoming period; h: the number of upcoming periods.

In this study, the parameters α and β are determined through a trial-and-error process, aiming to minimize the forecasting error based on the training data. The values that produce the smallest error metrics, such as the Mean Squared Error (MSE), are selected for model implementation (Hyndman & Athanasopoulos, 2018).

2.3. Scatter Plot, Autocorrelation Function (ACF), and Nonlinearity Test

In time series, information about the relationship in the data can be examined by a scatter plot diagram of the pair Y_t and Y_{t+k}, where the interval k is referred to as lag. A scatter plot of Y_t and Y_{t+1} that shows a random pattern indicates that the pair of an observation with the next observation is not correlated or does not have a strong linear relationship. However, if it makes a pattern of rising or falling lines, it indicates that the pair of an observation with the next observation is strongly correlated or has a strong linear relationship. The characteristics can also be identified using ACF by observing a linear relationship in the data based on the regression coefficient of itself with a lag in the period. The nonlinearity test is used to detect whether there is a nonlinear relationship in the data (Prabowo et al., 2020). One method of nonlinearity test is the white test developed by White in 1980 in the scope of NN model (Prabowo et al., 2020).

2.4. Box-Cox Transformation (BCT)

The BCT is usually used to transform a time series data to deal with non-constant variance or level differences in the data (Nwakuya & Nwabueze, 2018). The transformation considers a class of single-parameter transformations, i.e., λ, which is power transformed on the response variable y. Thus the transformation becomes y^{λ}. The concept of BCT is to find the optimal λ value so that the transformed data is closest to the normal distribution curve using Equation (4).

$$y_i^{\lambda} = \begin{cases} \dfrac{y_i^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \log\, y_i, & \lambda = 0 \end{cases} \tag{4}$$

2.5. Residual Diagnostic Test

Residual diagnostic test is used to prove that the model is good for forecasting testing data. With this test, it is possible to observe whether the residuals of the estimated model are autocorrelated and normally distributed or not. A model that satisfies the residual test condition has unautocorrelated residuals and normal residual distribution. If a forecasting method has serious deviations, it is necessary to rebuild another new model on the training data, which is then estimated and residual diagnostic tested again. One way to conduct a diagnostic test of residual autocorrelation is to use an ACF plot. Based on the visual of ACF plot, the residuals are uncorrelated if all lags are within the confidence interval. The normality test is conducted to determine whether the residuals generated by a forecasting method are normally distributed. The Anderson-Darling normality test is one of normality test methods (Ahmad & Khan, 2015) and is based on the test statistic A. The corrected version of the test statistic, denoted by A^*, adjusts A for sample size n and is calculated using the formula written in Equation (5),

$$A^* = A\left(1 + \frac{0.75}{n} + \frac{2.25}{n^2}\right) \tag{5}$$

The critical value is defined as $c_\alpha = a_\alpha(1 + \frac{b_0}{n} + \frac{b_1}{n^2})$ where $a_\alpha, b_0,$ and b_1 can be found on the critical values table by Kahya (1991). Testing the normality of residuals with the Anderson-Darling test statistic uses the following hypothesis

H_0: the residuals of the forecasting method have normal distribution,

H_1: the residuals of the forecasting method do not have normal distribution.

If $A^* > c_\alpha$, then H_0 is rejected which means that the residuals of the forecasting method do not have normal distribution. Conversely, if $A^* \leq c_\alpha$, then H_0 fails to be rejected which means that the residuals of the forecasting method have normal distribution.

2.6. Error Evaluation

In time series analysis, it is essential to evaluate how well the model performs. This can be done through the calculation of forecasting error evaluation. The evaluation methods used are RMSE, MAPE, and MPE which are formulated in Equations (6-8).

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \tag{6}$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{|e_t|}{|Y_t|} \times 100\% \tag{7}$$

$$\text{MPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{e_t}{Y_t} \times 100\% \tag{8}$$

where $e_t = Y_t - \hat{Y}_t$, the differences between the actual (Y_t) and the predicted $(\hat{Y}_t)$ value at time t.

3. MATERIAL AND METHOD

3.1. Dataset

This work considers the monthly closing stock price data of PT. Telkom Indonesia in 2005 to 2019 with a total of 180 observations from the id.investing.com website page. The proportion of training data used was 168 observations from January 2005 to December 2018 and 12 observations of testing data from January to December 2019.

3.2. Research Stages

Software used in this research is RStudio 4.1.2, Minitab 18, and MS. Excel. This research uses NNAR and DESH time series forecasting method. The outline of the research stages is shown in Figure 1.

The procedure for constructing the NNAR forecasting model involves two main stages. In the first stage, the model architecture is designed by determining the number of input nodes (autoregressive lags), the number of hidden units, and the activation functions. The number of inputs is selected based on the identified nonlinear relationships in the training dataset, as detected using the White test. A logistic activation function is applied in the hidden layer, while a linear activation function is used in the output layer to accommodate continuous forecasting targets.

In the second stage, the model weights are estimated using the backpropagation algorithm. In this work, an ensemble of 20 networks is trained, and their results are averaged to produce a stable and robust forecast. The final NNAR model is thus based on the autoregressive order ppp and the number of hidden neurons kkk, both determined through initial data exploration and architectural design.

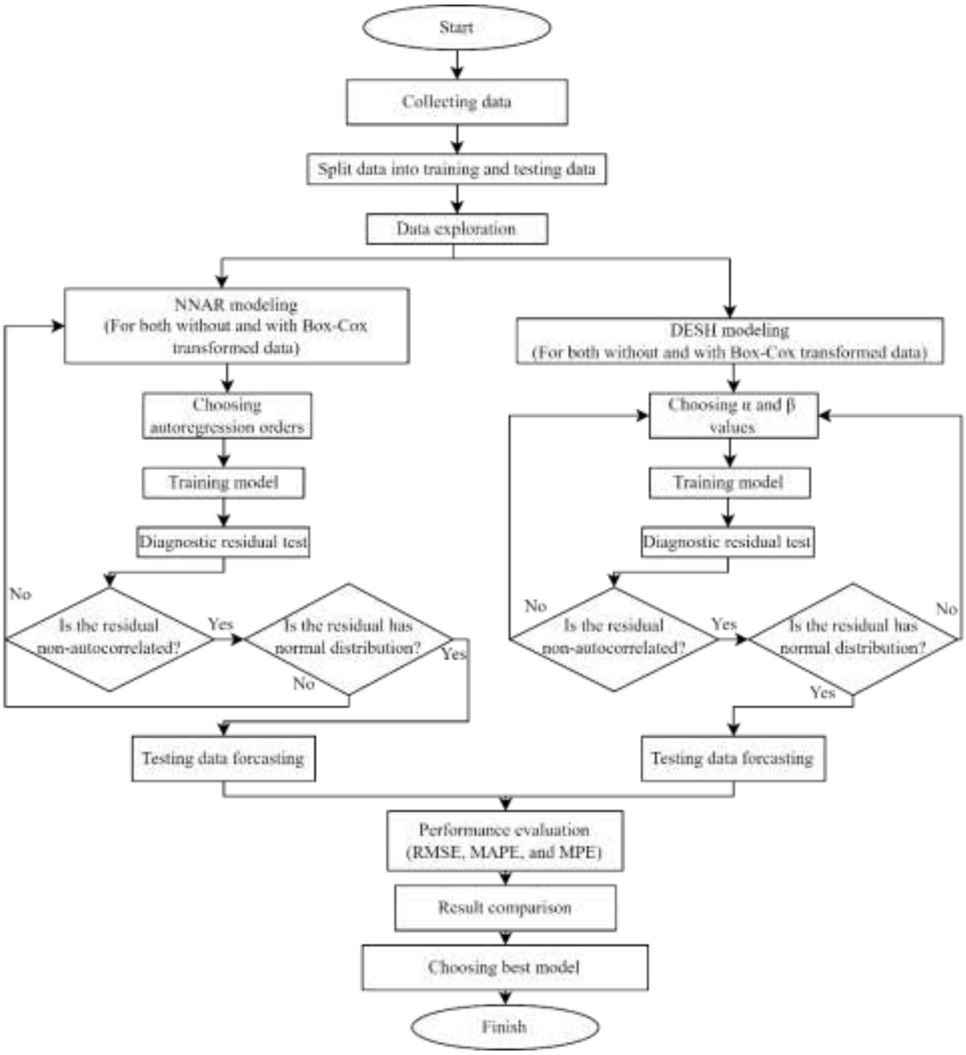

Figure 1. Flowchart of Research Stages

4. RESULTS AND DISCUSSION

Time series plot and ACF plot can be seen in Figures 2 and 3, respectively. The monthly closing stock price shows generally increasing prices from month to month which indicates a trend pattern (see Figure 2). Figure 3 also indicates there is a trend pattern in the data due to the slowly decreasing significant lag line.

Figure 2. The Monthly Closing Stock Price of PT Telkom Indonesia from January 2005 to December 2019

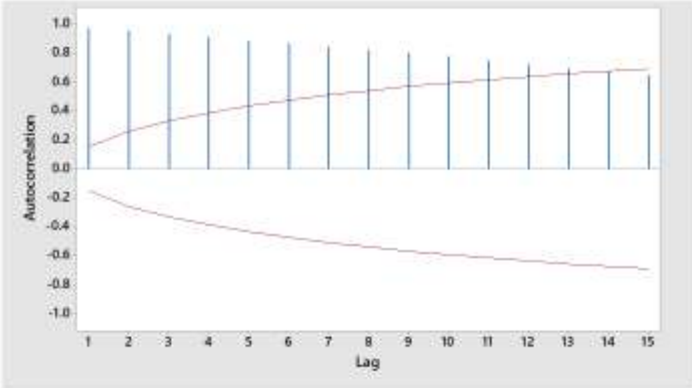

Figure 3. The ACF Plot for The Training Data

Table 1 presents the results of the White test for detecting nonlinearity between the current observation Y_t and its lagged values $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-6}$. The test indicates a significant nonlinear relationship at lag 1 (p-value = 0.017 < 0.05), while no significant nonlinearity is detected for higher lags. Based on these results, the NNAR(1,1) model is constructed by using one lagged input and one hidden neuron, which is deemed sufficient to capture the underlying nonlinear dynamics in the data.

Table 1. White Test Result

Lag	p-value	Description
1	0.017	Nonlinear relationship
2	0.893	Linear relationship
3	0.168	Linear relationship
4	0.110	Linear relationship
5	0.352	Linear relationship
6	0.431	Linear relationship

It is also needed to check whether the data has stable variability or variance using the Box-Cox plot. The results are presented in Table 2, and it was found that the data needs to be transformed twice.

Table 2. BCT Result

Data	Rounded Value λ	Description
Initial training data	0.5	Unstable variance
After the first transformation	0.5	Unstable variance
After the second transformation	1	Variance has stabilized

Based on the results of data exploration, the proposed NNAR model is specified as NNAR(1,1), consisting of one input node and one hidden node. A logistic activation function is applied in the hidden layer, while a linear activation function is used in the output layer. The NNAR(1,1) model can be expressed as:

$$\hat{Y}_t = v_{11}\left[1 + \mathrm{e}^{-(w_{11}Y_{t-1}+b_1)}\right]^{-1} + b_2$$

where w_{11} is the weight connecting the input node to the hidden node, v_{11} is the weight connecting the hidden node to the output, and b_1 and b_2 are the bias terms for the hidden and output layers, respectively. The specific values of b_1, b_2, v_{11}, and w_{11} are provided in Figures 4 and 5 for the models without and with Box-Cox Transformation (BCT), respectively. Additionally, the results of the residual diagnostic test for the NNAR(1,1) model, conducted at a significance level of 0.05, are presented in Table 3.

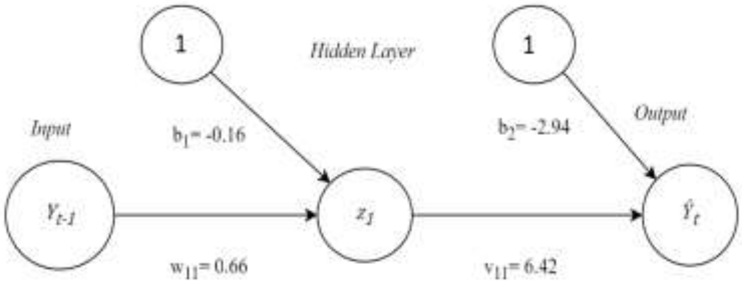

Figure 4. NNAR Model Architectures without BCT

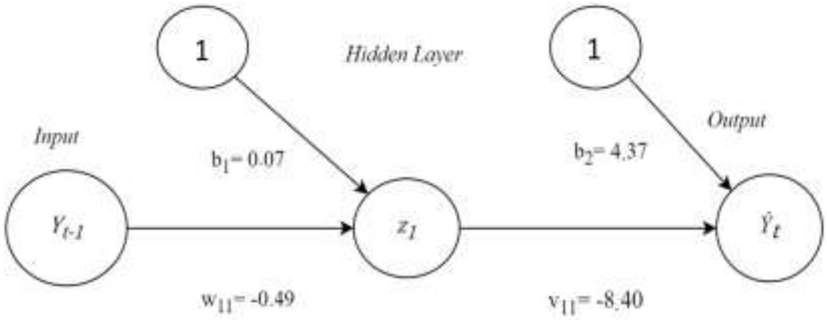

Figure 5. NNAR Model Architectures with BCT

Table 3. NNAR Residual Test Results

Data	Residual Autocorrelation Test	Residual Normality Test
NNAR(1,1) without BCT	Fulfilled	Fulfilled
NNAR(1,1) with BCT	Fulfilled	Fulfilled

The smoothing parameters α and β were selected through a trial-and-error process aimed at minimizing forecasting errors, particularly the Mean Squared Error (MSE) on the training dataset. The results of the residual diagnostic tests for several combination values of smoothing parameters of DESH are written in Table 4.

Table 4. Residual Test Results for DESH Model

DESH with parameters	Residual Autocorrelation Test	Residual Normality Test
α = 0.9 and β = 0.2	Fulfilled	Fulfilled
α = 0.6 and β = 0.2	Not Fulfilled	Not Fulfilled
α = 0.9 and β = 0.4	Not Fulfilled	Not Fulfilled

It shows that the DESH with smoothing constant parameter values α = 0.9 and β = 0.2 satisfies both the residual autocorrelation and residual normality tests. Therefore, the most appropriate DESH model for the data discussed in this study is expressed as

$$\hat{Y}_{t+h} = L_t + hT_t$$

where $L_t = 0.9Y_t + 0.1(L_{t-1} + T_{t-1})$

and $T_t = 0.2(L_t - L_{t-1}) + 0.8T_{t-1}$

Based on the analysis, three models fulfill the diagnostic test, namely the NNAR(1,1) model without and with Box-Cox transformation, and the DESH model with α = 0.9 and β = 0.2. For models developed with BCT, the forecasted values are re-transformed back to the original scale by applying the inverse Box-Cox transformation before evaluation and comparison. Figure 6 shows the comparison of forecast values calculated by NNAR and DESH models.

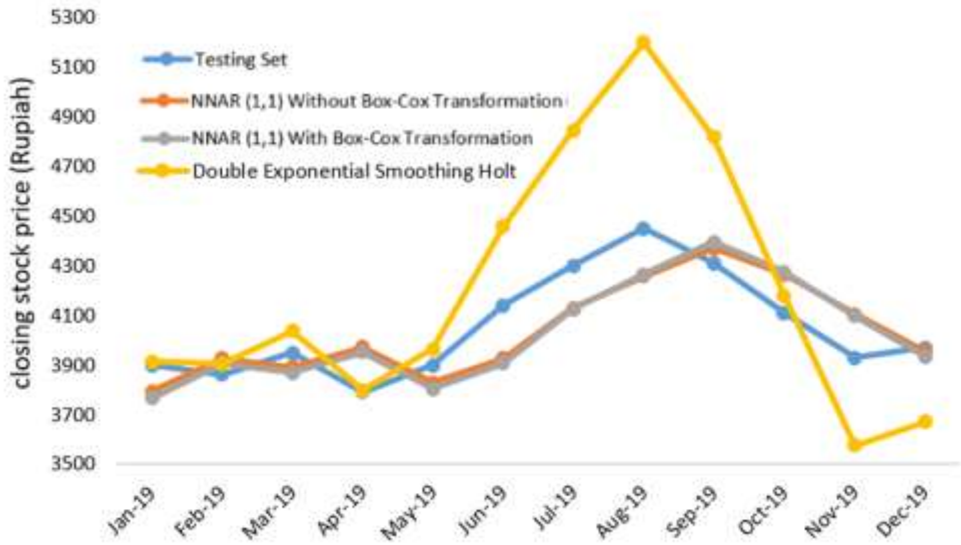

Figure 6. Comparison of Forecast Values Obtained from NNAR and DESH

Comparison of model error evaluation is shown in Table 5. Based on these comparison, the best forecasting model is NNAR(1,1) without Box-Cox transformation because it has the smallest error values for both training and testing data. The resulting MAPE have values of less than 10%, this indicating that the model has high accuracy. In addition, MPE values which are close to 0 indicates that the forecasting results are unbiased.

Table 5. Comparison of RMSEs and MAPEs Obtained from NNAR and DESH

Model	Training			Testing		
	RMSE	MAPE	MPE	RMSE	MAPE	MPE
NNAR(1,1) without BCT	3.12	5.42%	-0.50%	2.15	2.99%	0.32%
NNAR(1,1) with BCT	3.12	5.41%	-0.30%	2.23	3.20%	0.59%
DESH α=0.9 and β =0.2 without BCT	3.32	5.67%	-0.07%	5.30	6.05%	-3.30%
DESH α=0.9 and β =0.2 with BCT	3.31	5.65%	-0.23%	5.74	6.42%	-3.88%

5. CONCLUSION

This study investigated the implementation of Neural Network Autoregressive (NNAR) and Double Exponential Smoothing Holt (DESH) methods for modeling Telkom Indonesia’s stock price, focusing on whether applying Box-Cox Transformation (BCT) improves forecasting accuracy. The experimental results show that NNAR outperforms DESH in forecasting accuracy on the testing dataset. Specifically, the NNAR(1,1) model without BCT achieved RMSE, MAPE, and MPE values of 2.15, 2.99%, and 0.32%, respectively. Furthermore, it was found that applying BCT did not enhance the forecasting performance for either NNAR or DESH. Based on these findings, it can be concluded that BCT is not always necessary in time series modeling, particularly for forecasting Telkom Indonesia's stock price using NNAR and DESH methods.

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